Fuzzy Power Management for Energy Harvesting Wireless Sensor Nodes

Fayçal Ait Aoudia, Matthieu Gautier, Olivier Berder

Fuzzy Power Management for Energy Harvesting Wireless Sensor Nodes

Fayçal Ait Aoudia, Matthieu Gautier, Olivier Berder
University of Rennes 1, IRISA
Email: {faycal.ait-aoudia, matthieu.gautier, olivier.berder}@irisa.fr

***Abstract*—Power management is an important issue in the design of Energy Harvesting Wireless Sensor Networks (EH-WSNs). In this kind of networks, each Energy Harvesting Node (EH-node) must dynamically adapt its performance in order to avoid power failures while maintaining a good quality of service. The power management policy is implemented on each node by a Power Manager (PM). Designing a PM is challenging because the harvested energy is time varying, and the amount of energy that will be harvested in the future is hard to predict. In this work, we present Fuzzyman, a novel PM based on fuzzy control theory. Because of the unpredictability of the harvested energy, fuzzy control theory constitutes an appropriate framework to tackle the problem of designing PM for EH-nodes. We evaluate the performance of Fuzzyman by comparing it to a state of the art approach via extensive trace-driven network simulations. Results show that Fuzzyman achieves more efficient utilization of the harvested energy.**

I. Introduction

Sensors that constitute typical Wireless Sensor Networks (WSNs) are powered by individual batteries of limited capacity, and maximizing the lifetime of such systems is a perennial issue. Indeed, when the stored energy is exhausted, refilling the energy could be expensive or impossible if the network is dense or if the nodes are deployed in harsh environments. A more viable solution is to equip each node with at least one energy harvester, and to allow the sensors to be entirely powered by the energy harvested in their environments [1]–[7]. If the nodes perpetually operate in an *Energy Neutral* state [1], *i.e.* the amount of energy consumed never exceeds the amount of energy harvested over a long period of time, it is possible to significantly extend the lifetime of the network if the harvested energy is persistent.

If energy harvesting technologies enable the exploitation of renewable energy sources, a big challenge is the time-varying behavior of the harvested energy. Drained periods during which almost no energy is available can occur, for example during nighttime if solar energy is harvested. Therefore, in order to maintain a good quality of service during long periods, dynamic performance adaptation must be done using power management policies, implemented on each node by a PM. Many power management schemes were proposed in the last years, and they can be classified based on their requirement of predicted information about the amount of energy that can be harvested in the future, *i.e. prediction-based* and *model-free*.

As the name implies, prediction-based schemes require that an energy predictor [8] supplies the PM with predictions of the energy that can be harvested in the future. The first PM using the prediction-based approach was introduced in 2007 by *Kansal et al.* [1]. In their approach, the energy source is assumed to be pseudo-periodic, and an exponentially weighted moving average filter is used to predict the future amount of harvested energy. Then, the duty-cycle is computed by taking into account the difference between predicted and observed energy inputs. *Castagnetti et al.* introduced the Closed-Loop PM (CL-PM) in [3], which uses two distinct energy management strategies, one for periods during which environmental energy is available, and one for periods during which the harvested energy is below a fixed threshold, referred to as Zero Energy Interval (ZEI). The durations of ZEI are learned, in order to allow CL-PM to adjust the duty-cycle so that the node will not run into a power failure before the end of the non-harvesting interval. *Le et al.* proposed Wake up Variation Reduction PM (WVR-PM) in [4], a variation of CL-PM. The authors proposed an improvement that allows the node to store more energy when environmental energy is available for ZEI periods, in order to achieve similar quality of service during ZEI periods as when environmental energy is available. Moreover, WVR-PM does not require an additional sensor in order to approximate the harvested energy.

The amount of energy that a sensor can harvest shows large fluctuations and is hard to predict. As a consequence, energy predictors suffer from significant errors, which incur overuse or underuse of the harvested energy. Therefore, model-free schemes were proposed. These schemes do not require any prediction or model of the energy source in their power management strategies. The first model-free scheme was LQ-Tracker, introduced by *Vigorito et al.* in [2]. LQ-Tracker uses Linear-Quadratic Tracking, a technique from adaptive control theory, in order to adapt the duty-cycle considering only the state of charge of the energy storage device. Similarly, *Le et al.* proposed to use a Proportional Integral Derivative (PID) controller in [7]. With P-FREEN [6], *Peng et al.* proposed a PM that maximizes the duty-cycle of a sensor node in the presence of battery storage inefficiencies. The authors formulated the average duty-cycle maximization problem as a non-linear programming problem. As solving this kind of problem directly is computationally intense, they proposed a set of *budget assigning principles* that maximizes the duty-cycle by only using the current observed energy harvesting rate and the residual energy.

Fuzzy control theory aims to extend the existing conventional control system techniques and methods for a class of ill-modeled systems, *i.e.* fuzzy systems [9]. Because of the unstable and hard to predict behavior of the harvested energy, EH-nodes are usually hard to model systems. Therefore, fuzzy control theory constitutes an appropriate framework to design PM for EH-nodes. Accordingly, we propose in this work Fuzzyman, a PM for EH-nodes that relies on fuzzy control theory. Our contributions to the research on EH-WSNs are the following:

- Designing Fuzzyman, a PM for EH-nodes that is based on fuzzy control theory. To the best of our knowledge, this is the first work that uses this approach to tackle the problem of designing PM for EH-nodes.
- Tuning Fuzzyman in the case of EH-nodes powered by indoor ambient light using exhaustive trace-driven network simulations.
- Implementing and evaluating Fuzzyman and P-FREEN [6], a state of the art model-free PM that outperforms the reference scheme proposed by *Kansal et al.* [1], in the context of indoor ambient light energy harvesting using exhaustive trace-driven network simulations.

The rest of the paper is organized as follows. Section II presents Fuzzyman design. In Section III, the parameterization of Fuzzyman is discussed. The simulations results are presented in Section IV, and the paper concludes in Section V.

II. Designing Fuzzyman

A. System Model and Notations

Two methods currently exist to handle the harvested energy: harvest-store-use [5] and harvest-use (store) [10]. The first one consists of storing all the harvested energy and powering the node from the energy storage device only. However, due to energy storage inefficiencies, only a fraction of the harvested energy can be stored into energy storage devices, and this method therefore incurs important energy waste. This led to the proposal of the harvest-use (store) mechanism. The basic idea is to power the node directly from the harvested energy, and to store only the surplus of harvested energy. The node will draw energy from the energy storage device if the harvested energy is not sufficient. In this paper, we adopt the harvest-use (store) mechanism.

The time is divided into equal length time slots of duration T. The energy storage device is assumed to have a finite capacity denoted E_S^{max}. The hardware failing threshold is denoted E_S^{fail}, *i.e.* if the residual energy falls below this threshold, a power failure arises. The leakage power and the power conversion efficiency are assumed to be constant and are denoted P_L and $\eta \in (0, 1]$ respectively. The amount of energy required to ensure the desired minimum quality of service for one time slot is denoted E_B^{min}. When the node is in energetic distress *i.e.* in a high risk to run into a power failure, it goes into *energetic distress state* and the amount of energy required to ensure minimal operation for one time slot in this state is denoted E_B^{eds} such that $E_B^{eds} < E_B^{min}$.

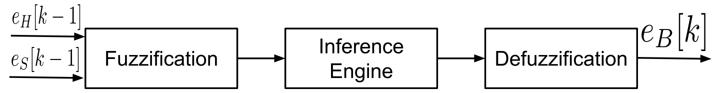
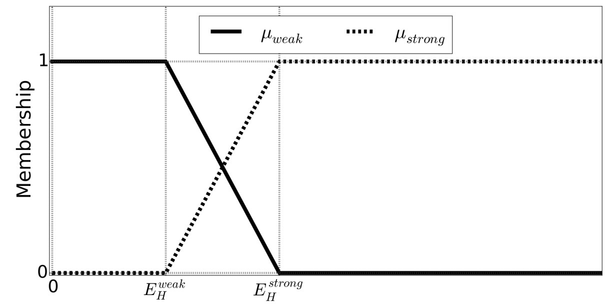
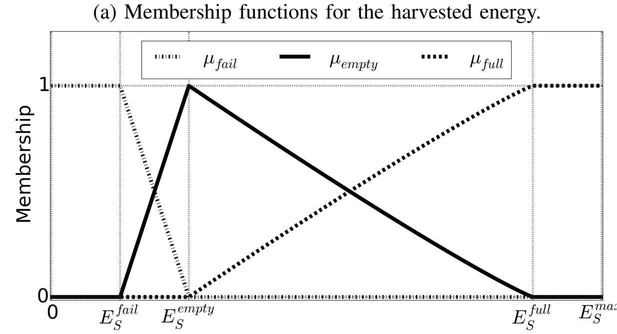


Fig. 1: Global architecture of Fuzzyman.



(a) Membership functions for the harvested energy.



(b) Membership functions for the residual energy.

Fig. 2: Membership functions used by the fuzzification module.

B. Fuzzyman global architecture

The task of Fuzzyman is to compute the energy budget $e_B[k]$ that the node should use during the slot k regarding the residual energy at the end of the previous time slot $e_S[k-1]$ and the energy harvested during the previous time slot $e_H[k-1]$. Therefore, Fuzzyman is executed at the end of every time slot. As a fuzzy logic controller [9], Fuzzyman is made of three units: the fuzzification unit, the inference engine, and the defuzzification unit as shown by Fig. 1. The fuzzification module is the input terminal. Its job is to transform the physical inputs into fuzzy sets compatible with the inference engine. A fuzzy set consists of an interval for the range of the input value and an associate normalized membership function describing the degree of the confidence of the input belonging to this range. The inference engine is the core of the controller. It is responsible for creating the control actions in fuzzy terms. Finally, the defuzzification unit maps the controller outputs to a physical value that can be accepted by the node. In the rest of this section, these three modules are described in detail.

C. Fuzzification of the Controller Inputs

The first module of Fuzzyman is the fuzzification unit, which converts each input physical value, *i.e.* $e_S[k-1]$ and $e_H[k-1]$, into fuzzy sets.

Harvested Energy Fuzzification: To describe the harvested energy physical value $e_H \geqslant 0$, two fuzzy sets named "WEAK" and "STRONG" are considered. They are associated to the following normalized membership functions, shown by Fig. 2a:

$$\mu_{weak}(x) = \begin{cases} 1, & \text{if } x \leqslant E_H^{weak} \\ \frac{-x+E_H^{strong}}{E_H^{strong}-E_H^{weak}}, & \text{if } E_H^{weak} < x < E_H^{strong} \\ 0, & \text{if } x \geqslant E_H^{strong} \end{cases} \quad (1)$$

$$\mu_{strong}(x) = \begin{cases} 0, & \text{if } x \leqslant E_H^{weak} \\ \frac{x-E_H^{weak}}{E_H^{strong}-E_H^{weak}}, & \text{if } E_H^{weak} < x < E_H^{strong} \\ 1, & \text{if } x \geqslant E_H^{strong} \end{cases} \quad (2)$$

where E_H^{weak} is equal to the amount of energy required to ensure the minimum quality of service for one time slot, when the power conversion efficiency and the leakage are taken into account, *i.e.*:

$$E_H^{weak} = \frac{E_B^{min}}{\eta} + P_L T. \quad (3)$$

Thus, if the source is fully "WEAK", then the amount of harvested energy is not enough to provide the minimum energy budget E_B^{min}. E_H^{strong} is the threshold at which the harvested energy is considered to be fully "STRONG".

Residual Energy Fuzzification: Three fuzzy sets are used to describe the residual energy e_S, which is within the range $[0, E_S^{max}]$. These fuzzy sets, named "FAIL", "EMPTY" and "FULL", are associated to the following membership functions, shown by Fig. 2b:

$$\mu_{fail}(x) = \begin{cases} 1, & \text{if } x \leqslant E_S^{fail} \\ \frac{-x+E_S^{empty}}{E_S^{empty}-E_S^{fail}}, & \text{if } E_S^{fail} < x < E_S^{empty} \\ 0, & \text{if } x \geqslant E_S^{empty} \end{cases} \quad (4)$$

$$\mu_{empty}(x) = \begin{cases} 0, & \text{if } x \leqslant E_S^{fail} \\ \frac{x-E_S^{fail}}{E_S^{empty}-E_S^{fail}}, & \text{if } E_S^{fail} < x \leqslant E_S^{empty} \\ f_K(x), & \text{if } E_S^{empty} < x < E_S^{full} \\ 0, & \text{if } x \geqslant E_S^{full} \end{cases} \quad (5)$$

$$\mu_{full}(x) = \begin{cases} 0, & \text{if } x \leqslant E_S^{empty} \\ 1 - f_K(x), & \text{if } E_S^{empty} < x < E_S^{full} \\ 1, & \text{if } x \geqslant E_S^{full} \end{cases} \quad (6)$$

where

$$f_K(x) = \left(\frac{-x + E_S^{full}}{E_S^{full} - E_S^{empty}} \right)^K, \quad (7)$$

and $K \geqslant 0$ controls the shapes of the membership functions μ_{full} and μ_{empty}. The higher K is, the faster μ_{full} tends to 1 and μ_{empty} tends to 0 when the residual energy increases. Therefore, choosing high values of K makes Fuzzyman more tolerant about the fullness of the energy storage device. We denote E_R the amount of energy that is needed to be reserved in order for the node to ensure the minimum quality of service when no harvested energy is available. E_S^{full} indicates that the node has reserved sufficient energy E_R. E_S^{empty} indicates that all the reserved energy E_R was used up. Thus, $E_R = E_S^{full} - E_S^{empty}$. Having $E_S^{empty} > E_S^{min}$ avoids power failure when all the reserved energy has been used. When the amount of residual energy falls below E_S^{empty}, the node enters the *energy distress state*. Finally, having $E_S^{full} < E_S^{max}$ avoids wasting energy by overflow of the storage device.

D. Inference Engine

The task of the inference engine is to create the control actions in fuzzy terms according to the fuzzy inputs provided by the fuzzification module. The inference engine strategy is described by a set of 6 fuzzy IF-THEN rules R_i with $i \in \{1 \dots 6\}$ shown by the TABLE I. For each slot k, the output of the rule i is denoted $e_B^i[k]$. The output of the rules R_2 and R_3 are given by (8), and the rule R_6 output is the energy budget used at the previous slot.

e_H \ e_S	FAIL	EMPTY	FULL
STRONG	E_B^{eds} (R_1)	(8) (R_2)	(8) (R_3)
WEAK	E_B^{eds} (R_4)	E_B^{min} (R_5)	$e_B[k-1]$ (R_6)

TABLE I: Rule base used by the inference engine.

$$e_B^i[k] = E_B^{min} + \mu_{full}\left(e_S[k-1]\right) \left(e_H[k-1] - \frac{E_B^{min}}{\eta} - P_L T \right) \eta. \quad (8)$$

In (8), it is assumed that the energy harvesting rates for two consecutive time slots are similar. This assumption is reasonable for sufficiently small time slot duration. Energy prediction schemes can be used for better estimation of the energy harvesting rate in near future [8].

All rules contain the fuzzy logic AND operation, and share the following multi-input single-output form: "IF ($e_S[k-1]$ is X_S^i) AND ($e_H[k-1]$ is X_H^i) THEN $e_B[k]$ is $e_B^i[k]$", where the phrase "x is X" is an abbreviation for the complete statement "x belongs to the fuzzy set X with a membership value $\mu_X(x)$", X_S^i can be either FAIL, EMPTY or FULL and X_H^i can be either STRONG or WEAK. It is important to notice that up to four rules can be activated at one run of Fuzzyman. The power strategy implemented by TABLE I corresponds to five different scenarios:

1) R_1 and R_4: If the residual energy is FAIL, then the node is in energy distress. In that case, the energy budget is set to E_B^{eds}.
2) R_5: If the amount of harvested energy is WEAK and the energy storage device is EMPTY, then the energy budget is set to the amount of energy required to ensure minimum quality of service, *i.e.* E_B^{min}.
3) R_6: If the amount of harvested energy is WEAK and the energy storage device is FULL, then the energy budget is unchanged.
4) R_2: If the amount of harvested energy is STRONG and the energy storage device is not yet fully charged, *i.e.* $\mu_{full}(e_S[k-1]) < 1$, then part of the harvested energy is used to power the node, while the rest is stored. The fraction of the harvested energy used to power the node will be at least E_B^{min}, and depends on μ_{full} as shown by (8). Therefore, K controls the energy allocation policy of Fuzzyman.
5) R_3: If the amount of harvested energy is STRONG and the energy storage device is fully charged, *i.e.*

$\mu_{full}(e_S[k-1]) = 1$, then only the amount of energy required to compensate for the leakage is stored, while the rest is used to power the node, thus minimizing the risk of energy waste.

The fuzzy AND operator is implemented by the $\mathtt{min}$ function [9]. The *activation value* $\mu_R^i[k] \geqslant 0$ for each rule R_i is defined by:

$$\mu_R^i[k] = \mathtt{min}\left\{\mu_{X_S^i}\left(e_S[k-1]\right), \mu_{X_H^i}\left(e_H[k-1]\right)\right\}. \quad (9)$$

The rule R_i is *activated* if its activation value is strictly positive. If the rule is not activated, then its output value $e_B^i[k]$ is simply set to 0. At every run of Fuzzyman, at least one rule is activated, and thus:

$$\sum_{i=1}^{6} \mu_R^i[k] > 0. \quad (10)$$

The activation value of each rule is interpreted as the membership value of the energy budget to the output of the rule. The importance of K can be seen here. Indeed, the K parameter controls the membership functions of the FULL and EMPTY fuzzy sets, and therefore impacts the activation values of the rules. The highest K is, the more tolerant is Fuzzyman about the fullness of the energy storage device, and therefore the less prudent it is. In Section III, the choice of the adequate value of K in the context of indoor ambient light harvesting is considered.

E. Defuzzification of the Energy Budget

The last unit of Fuzzyman is the defuzzification unit, which computes a physical value of the energy budget from the outputs of the inference engine. The "center-of-gravity" is the most common formula [9] to perform defuzzification. Thus, the physical value of the energy budget is computed by:

$$e_B[k] = \frac{\sum_{i=1}^{6} \mu_R^i[k] e_B^i[k]}{\sum_{i=1}^{6} \mu_R^i[k]}, \quad (11)$$

which can always be computed according to (10).

Finally, the algorithm of Fuzzyman is shown by Algorithm 1. The complexity of the proposed algorithm is $O(1)$, and incurs very few computations and memory overhead. Therefore, it is well-adapted to wireless sensor nodes.

Algorithm 1 Fuzzyman algorithm

Input: $e_S[k-1]$, $e_H[k-1]$
  $i \leftarrow 1$
  while $i \leqslant 6$ **do**
    $\mu_R^i[k] \leftarrow \mathtt{min}\{\mu_{X_S^i}(e_S[k-1]), \mu_{X_H^i}(e_H[k-1])\}$
    if $\mu_R^i[k] > 0$ **then**
      Set $e_B^i[k]$ according to TABLE I
    else
      $e_B^i[k] \leftarrow 0$
    $i \leftarrow i+1$
  $e_B[k] \leftarrow \frac{\sum_{i=1}^{6} \mu_R^i[k] e_B^i[k]}{\sum_{i=1}^{6} \mu_R^i[k]}$
  return $e_B[k]$

III. Tuning Fuzzyman

The K parameter is the control parameter of Fuzzyman. Choosing K inappropriately may lead to power failures or energy waste. The adequate value of K depends on both the energy source and the energy storage device capacity E_S^{max}. We focus on the PowWow platform [11], which embeds a 0.9 F supercapacitor. Moreover, EH-nodes powered by indoor ambient light are considered in this work. Ambient light is the most common and mature among the different forms of energy harvesting. Indoor ambient light is usually a diurnal energy source, and the typical illumination level varies from 1 W/m^2 [12] to 10 W/m^2 [13]. Simulations are used to find the adequate value of K when the PowWow platform is used and when indoor ambient light is harvested.

A. Simulation setup

Simulations were done using GreenCastalia [14], an open-source energy harvesting simulation framework for the Castalia/OMNeT++ simulator [15]. The simulated network consists of one sink that uses batteries as energy supply, and four EH-nodes powered by solar cells. The solar panel area is set to 28 cm^2, and the panel efficiency to 15%, which is a realistic value regarding current photovoltaic technologies [16]. The simulated platform embeds a TI CC1000 radio chip, which consumes 22.2 mW in receive state, 80.1 mW in transmit state and 0.0006 mW in sleep state. Because we want to evaluate the performance of the PM, only the energy waste due to energy storage device saturation *i.e.* harvested energy that cannot be stored because the energy storage device is full, is considered. Therefore, the power conversion efficiency η is set to 1 and the leakage power P_L is set to 0 W. Moreover, T is set to 300 s, and each simulation last 31 days (simulated time).

The energy consumption of the EH-node is controlled by duty-cycling [17]. As communication is usually the most consuming task, the idea of duty-cycling is to allow the node to switch its radio between the sleep state and the active state according to a schedule. At each wake up, the sensor node performs a measurement and sends the so obtained value to the sink. Environmental power sources provide energy that varies with time and space, leading to decoupled and individual duty-cycle among EH-nodes. This makes synchronous MAC protocols unsuitable to EH-WSNs as they require synchronized duty-cycle [18]. In [19], we have shown that a simple CSMA/CA MAC protocol leads to lower energy consumption than the TMAC protocol that Castalia proposes. Therefore, this protocol is used in this work. E_B^{min} is set to 0.0221 J which corresponds to a minimal wake up frequency of $1/60$ Hz.

B. Energy traces

GreenCastalia needs energy traces in order to simulate the harvested energy. In our previous work [19], a trace generation algorithm that generates diurnal traces was proposed. The purpose of the trace generation algorithm is to evaluate PMs in regards to energy source characteristics that influence significantly their behaviors, and which can be set by the user

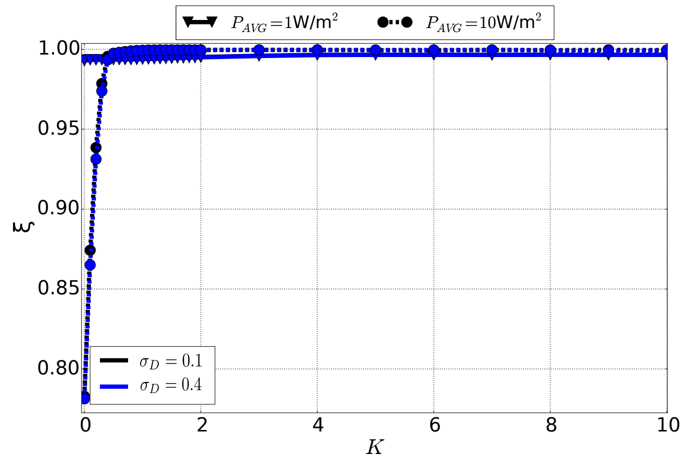


Fig. 3: Energy utilization efficiency ξ as a function of K.

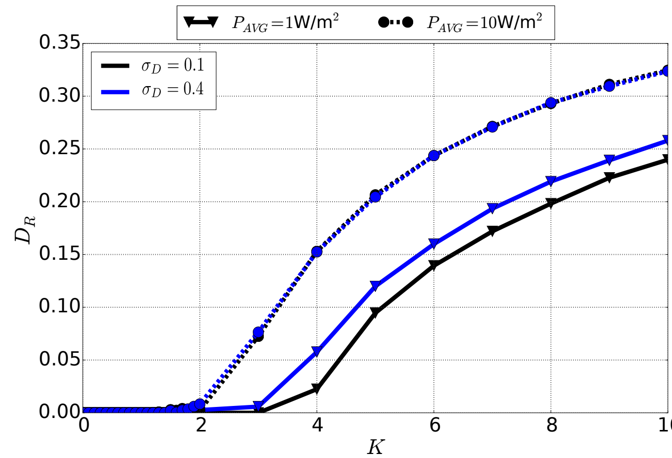


Fig. 4: Downtime ratio D_R as a function of K.

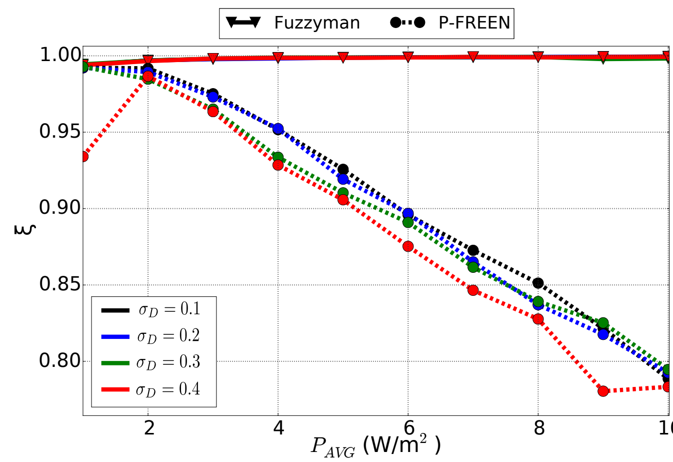


Fig. 5: Energy utilization efficiency ξ as a function of P_{AVG} for different values of σ_D.

using input parameters of the proposed model. Particularly, the P_{AVG} parameter allows to set the average harvested power during daytime, and σ_D allows to control the intensity of the fluctuations of the harvested power from one day to the other. In the case of ambient light harvesting, typical power densities range from 1 W/m^2 [12] to 10 W/m^2 [13]. Therefore, using the trace generation algorithm, two pairs of energy traces were generated, one with P_{AVG} set to 1 W/m^2 and one with P_{AVG} set to 10 W/m^2. Each pair is made of two energy traces, one with important fluctuations generated with σ_D set to 0.4, and one with low fluctuations generated with σ_D set to 0.1.

C. Simulations results

Two metrics are considered for the choice of K: the downtime ratio D_R corresponding to the ratio of time spent in the power failure state, and the energy utilization efficiency ξ, defined as the ratio of the total energy used by the node over the total energy harvested. This metric is similar to the harvested energy utilization introduced in [6].

Fig. 3 and Fig. 4 show respectively ξ and D_R for values of K ranging from 0 to 10. We can see that for values of K higher than 0.4, the energy efficiency is higher than 0.99 for the four scenarios, while for smaller values of K the energy efficiency is significantly lower when $P_{AVG} = 10$ W/m^2. These results reveal that using low values of K can prevent Fuzzyman from taking advantage of all the harvested energy. Nonetheless, using too high values of K causes Fuzzyman to incur power failures. Indeed, Fig. 4 shows that for values of K greater than 1.1 the downtime ratio stop being null and increases rapidly. According to these results, $K = 1.1$ is the value that maximizes ξ while achieving a null downtime ratio for the four traces introduced in Section III-B. Therefore, this value of K is chosen for the evaluation of Fuzzyman presented in Section IV. Fig. 2 shows the membership functions when $K = 1.1$.

IV. Evaluating Fuzzyman

We compare Fuzzyman to P-FREEN [6], a state of the art model-free PM that outperforms the reference scheme proposed by *Kansal et al.* [1]. The simulation setup is the same as in Section III-A. Simulations were done with energy traces generated by the model introduced in Section III-B. Two metrics in addition to D_R and ξ are considered: the wasted energy E_{WST}, *i.e.* the harvested energy that could not be stored because the energy storage device was full, and the average energy budget $\overline{E_B}$. Simulations were run for values of P_{AVG} ranging from 1 W/m^2 to 10 W/m^2, and values of σ_D ranging from 0.1 to 0.4. Both Fuzzyman and P-FREEN achieve downtime ratio lower than 0.2 % in all the simulation scenarios. Therefore, we focus on the energy utilization efficiency, the wasted energy and the average energy budget in the rest of this section.

Fig. 5 exposes the impact of P_{AVG} and σ_D on ξ. If ξ is similar for both PMs when $P_{AVG} = 1$ W/m^2, Fuzzyman outperforms P-FREEN for higher values of P_{AVG}. σ_D has no impact on the performance of the PMs, whereas high values of P_{AVG} lead to lower values of ξ for P-FREEN, but do not influence the performance of Fuzzyman. As we will see below, these results are explained by the larger waste of energy incurred by P-FREEN.

Fig. 6 shows the wasted energy E_{WST} when P_{AVG} and σ_D vary. As we can see, Fuzzyman incurs significantly less energy waste than P-FREEN. As previously, σ_D does not impact the

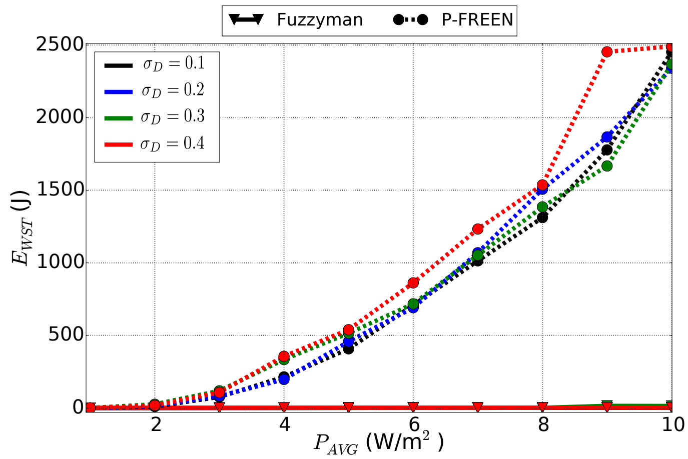


Fig. 6: Wasted energy E_{WST} as a function of P_{AVG} for different values of σ_D.

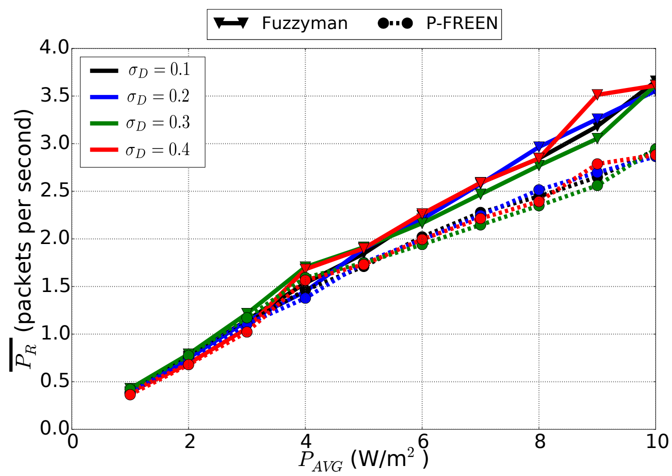


Fig. 7: Average packet rate $\overline{P_R}$ as a function of P_{AVG} for different values of σ_D.

performance of the PMs. When P_{AVG} increases, the amount of wasted energy increases when P-FREEN is used, but stays low when Fuzzyman is used. This result explains the values of ξ exposed by Fig. 5.

In order to evaluate the impact of the more efficient harvested energy management achieved by Fuzzyman, the average packet rate $\overline{P_R}$ is considered. Fig. 7 shows the impact of P_{AVG} and σ_D on $\overline{P_R}$. If the average energy budget is similar for both PMs for low values of P_{AVG}, Fuzzyman outperforms P-FREEN for high values of P_{AVG}. Moreover, the advantage of Fuzzyman over P-FREEN increases when P_{AVG} increases. Indeed, Fuzzyman achieves up to 25% higher $\overline{P_R}$ than P-FREEN (when $P_{AVG} = 10\,\text{mW}$ and $\sigma_D = 0.4$).

V. Conclusion

This paper presents the design and evaluation of Fuzzyman, a novel PM for EH-nodes based on fuzzy control theory. Fuzzyman is able to provide high harvested energy utilization efficiency, while avoiding power failures. This work presents the evaluation of Fuzzyman when compared to P-FREEN, a state of the art PM. Using extensive trace driven network simulations, we have shown that Fuzzyman outperforms P-FREEN in terms of harvested energy utilization efficiency. In our future work, we intend to implement Fuzzyman on real hardware platforms.

References

[1] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava, "Power Management in Energy Harvesting Sensor Networks," *ACM Transactions on Embedded Computing Systems*, vol. 6, no. 4, 2007.

[2] C. Vigorito, D. Ganesan, and A. Barto, "Adaptive Control of Duty Cycling in Energy-Harvesting Wireless Sensor Networks," in *4th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON)*, June 2007.

[3] A. Castagnetti, A. Pegatoquet, C. Belleudy, and M. Auguin, "A framework for modeling and simulating energy harvesting WSN nodes with efficient power management policies," *EURASIP Journal on Embedded Systems*, no. 1, 2012.

[4] T. N. Le, A. Pegatoquet, O. Berder, and O. Sentieys, "Energy-Efficient Power Manager and MAC Protocol for Multi-Hop Wireless Sensor Networks Powered by Periodic Energy Harvesting Sources," *IEEE Sensors Journal*, vol. 15, no. 12, pp. 7208–7220, 2015.

[5] S. Sudevalayam and P. Kulkarni, "Energy Harvesting Sensor Nodes: Survey and Implications," *IEEE Communications Surveys & Tutorials*, vol. 13, no. 3, pp. 443–461, March 2011.

[6] S. Peng and C. Low, "Prediction free energy neutral power management for energy harvesting wireless sensor nodes," *Ad Hoc Networks*, vol. 13, Part B, 2014.

[7] T. N. Le, O. Sentieys, O. Berder, A. Pegatoquet, and C. Belleudy, "Power Manager with PID Controller in Energy Harvesting Wireless Sensor Networks," in *IEEE International Conference on Green Computing and Communications (GreenCom)*, 2012.

[8] J. Piorno, C. Bergonzini, D. Atienza, and T. Rosing, "Prediction and Management in Energy Harvested Wireless Sensor Nodes," in *1st International Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace Electronic Systems Technology. (Wireless VITAE)*, May 2009.

[9] G. Chen and T. T. Pham, *Introduction to Fuzzy Sets, Fuzzy Logic, and Fuzzy Control Systems*. CRC Press, 2000.

[10] S. Peng and C. P. Low, "Throughput optimal energy neutral management for energy harvesting wireless sensor networks," in *IEEE Wireless Communications and Networking Conference (WCNC)*, April 2012.

[11] "PowWow: Power Optimized Hardware and Software FrameWork for Wireless Motes," http://powwow.gforge.inria.fr/, 2014, [Online; accessed December-2015].

[12] J. Paradiso and T. Starner, "Energy scavenging for mobile and wireless electronics," *IEEE Pervasive Computing*, vol. 4, no. 1, pp. 18–27, Jan 2005.

[13] C. Ó. Mathúna, T. O'Donnell, R. V. Martinez-Catala, J. Rohan, and B. O'Flynn, "Energy scavenging for long-term deployable wireless sensor networks," *Talanta*, vol. 75, no. 3, pp. 613 – 623, 2008, Special Section: Remote Sensing.

[14] D. Benedetti, C. Petrioli, and D. Spenza, "GreenCastalia: An Energy-harvesting-enabled Framework for the Castalia Simulator," in *Proceedings of the 1st ACM International Workshop on Energy Neutral Sensing Systems (ENSSys)*, 2013.

[15] A. Boulis, "Castalia: Revealing Pitfalls in Designing Distributed Algorithms in WSN," in *Proceedings of the 5th International Conference on Embedded Networked Sensor Systems (SenSys)*, 2007.

[16] M. A. Green, K. Emery, Y. Hishikawa, W. Warta, and E. D. Dunlop, "Solar cell efficiency tables (version 45)," *Progress in Photovoltaics: Research and Applications*, vol. 23, no. 1, pp. 1–9, 2015.

[17] G. Anastasi, M. Conti, M. D. Francesco, and A. Passarella, "Energy conservation in wireless sensor networks: A survey," *Ad Hoc Networks*, vol. 7, no. 3, pp. 537 – 568, 2009.

[18] X. Fafoutis and N. Dragoni, "Analytical comparison of MAC schemes for Energy Harvesting - Wireless Sensor Networks," in *Ninth International Conference on Networked Sensing Systems (INSS)*, June 2012.

[19] F. Ait Aoudia, M. Gautier, and O. Berder, "GRAPMAN: Gradual Power Manager for Consistent Throughput of Energy Harvesting Wireless Sensor Nodes," in *IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, September 2015.